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Forecasting annual cyanobacterial bloom biomass to inform management decisions in Lake Erie

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ABSTRACT

Blooms of the toxic cyanobacteria, *Microcystis aeruginosa*, have been both a public health and ecological concern in Lake Erie for over a decade. Although models were previously developed to forecast cyanobacterial bloom severity, the recent few years of bloom severity observations indicate the need to update these empirical models. The models that best estimate the bloom biomass use the Maumee River discharge or total bioavailable phosphorus (TBP) loading from March through July. TBP is the sum of the dissolved reactive phosphorus and the proportion of particulate phosphorus that is bioavailable, corrected for loss due to settling in the river. In years when average June water temperatures were too low for *Microcystis* growth (<17 °C), the July loads were excluded. As total phosphorus (TP) load includes much phosphorus that is not bioavailable (or reaches the lake), the load of TBP was considered, and it provided a model that better explained the blooms than the TP load. Residual discrepancies between predicted and observed blooms may involve factors such as the timing of the majority of the spring loads (e.g., most in March or most in June or July) and potential influence from an extremely large bloom in the previous year. The most extreme loads, such as seen in 2015, may cause different responses than more moderate loads. The models estimate bloom size in most scenarios observed and can serve as the foundation for setting nutrient reduction targets to decrease the occurrence of blooms in western Lake Erie.

Introduction

For over a decade, western Lake Erie has experienced the recurrence of dense blooms of cyanobacteria, or blue-green algae. These harmful "algal" blooms (HABs) have consisted primarily of *Microcystis aeruginosa* (henceforth referred to as *Microcystis*), an organism that produces the toxin microcystin, but they have also included other potential toxin producers such as *Dolichospernum* spp. and *Planktothrix agardhii* (the latter more common in bays off the main lake). Lake Erie experienced severe cyanobacteria blooms in the 1960s and 1970s. In the 1980s and 1990s, the lake appeared to be bloom free, except for blooms reported in 1995 and 1998 (Budd et al., 2001; Kane et al., 2014). Starting in 2003, HABs became an annual occurrence, although the severity varied widely between years (Bridgeman et al., 2013; Stumpf et al., 2012). Recently, the occurrence of HABs has culminated in several exceptional years: 2011, 2013, 2014, and 2015. The 2011 bloom may have been the most extensive ever to occur in Lake Erie to that time, ultimately covering over 5000 km^2 of the lake and impacting both the American and Canadian coasts (Michalak et al., 2013; Stumpf et al., 2012). The 2011 bloom had a widespread influence impacting fishing, tourism, and public water suppliers. In 2013 and 2014, potentially hazardous concentrations ($>1\ \mu g\ L^{-1}$) of microcystin were detected in finished drinking water of communities adjacent to western Lake Erie. In 2013, Carroll Township issued a "do-not-use" advisory to its 2000 municipal water supply customers, and in 2014, the city of Toledo had the same problem, resulting in a "do-not-drink" notice for 3 days to about a half-million people. The 2015 bloom was estimated to be even more severe than 2011 (NOAA, 2015).

In order to reduce the impacts caused by western Lake Erie HABs, several strategies have been employed to address management issues at different time scales. In the short term, biweekly forecast bulletins are produced that show the location and intensity of the bloom over the next few days (Wynne et al., 2013a). These bulletins provide information that can support immediate action for drinking water treatment. They also help activities such as boating, fishing, and other tourism that can move based on bloom location. In the mid-term, a seasonal forecast of the bloom severity allows public water suppliers and agencies concerned with toxin monitoring to plan for the bloom season, and for local businesses to anticipate possible effects on the summer tourism economy (Stumpf et al., 2012). In the long term, being able to forecast HAB intensity on an annual basis helps identify the management actions

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that could reduce or eliminate the blooms in the future (Ohio EPA, 2013; Scavia et al., 2016-in this issue), which is the emphasis of this manuscript.

Short-term forecasts of the blooms have been in place since 2009 through the Lake Erie Experimental Harmful Algal Bloom Forecast System (Wynne et al., 2010, 2013a), which is produced and distributed by the U.S. National Oceanic and Atmospheric Administration (NOAA, 2015). This forecast includes determination of bloom location and intensity from satellite and the use of a circulation model to predict the location several days into the future. As of September 2015, the bulletin was issued as the key part of the forecast and had over 1500 subscribers.

Seasonal forecasts were developed out of an examination of the factors that should drive the blooms. Stumpf et al. (2012) showed that the spring (March to June) discharge from the Maumee River (Fig. 1), as well as total phosphorus (TP) or dissolved reactive phosphorus (DRP) loads, explained the interannual variability in blooms since 2002. Using the same data, but a different statistical approach, Obenour et al. (2014) also concluded that spring TP load explained the bloom severity although they also proposed that there was a trend toward increasing bloom magnitude over time. The Stumpf et al. (2012) model was used to predict blooms in 2012 and 2013 up to 2 months in advance of the peak concentration (NOAA, 2012, 2013). In the last 2 years, the annual forecast drew on an ensemble of models, including Obenour et al. (2014) and the deterministic model of Verhamme et al. (2016-in this issue) (NOAA, 2014, 2015).

For the long term, modeling the bloom severity can support determination of targets for nutrient loads that can reduce the bloom. The 1972, Great Lakes Water Quality Agreement (GLWQA) set annual target loads for TP at 11,000 metric tons in order to reduce the blooms occurring at that time. The recurrence of blooms has shown that these targets are outdated, in part because this target was first met in 1981 and also because it has rarely been exceeded even in the recent bloom years (Ohio EPA, 2013). The most recent GLWQA (2012) calls for a rigorous update to the targets for phosphorus reductions in order to reduce the incidence of extreme HABs in the western basin (Ohio EPA, 2013; GLWQA, 2012). Phosphorus-based models are critical to determining targets for phosphorus reduction. Climatological models, such as Stumpf et al. (2012) provide a key component of a multi-model strategy to increase management confidence in the robustness of phosphorus reduction scenarios (Scavia et al., 2016-in this issue).

In considering models linking phosphorus loads to HAB severity, an additional consideration is the relative importance of various forms of phosphorus delivery, given that particulate phosphorus and dissolved phosphorus can have drastically differing bioavailability (Baker et al., 2014a). In the Maumee River, about 26% of the total particulate phosphorus (TPP) is chemically bioavailable, whereas nearly 100% of the dissolved phosphorus is bioavailable (Baker et al., 2014a). In the 1970s, when most phosphorus came from point sources like sewage treatment plants, most TP discharged into the lake was bioavailable. Following reductions in point sources of phosphorus (P) and changes in agricultural practices, nonpoint sources from agricultural land now dominate TP loads to Lake Erie. For the Maumee River, TP consists of 73% particulate P—mostly bound to suspended sediments—and 27% DRP (Baker et al., 2014a). Furthermore, some 70% of TPP is spatially unavailable, as it settles out of the water over the 42 km transit from the nutrient sampling station (and water gauge) at Waterville, Ohio, to the mouth of the Maumee River in Lake Erie (Baker et al., 2014b). Hence, less than half of the TP measured in the Maumee River is immediately available to phytoplankton in the lake.

The original models in Stumpf et al. (2012) were developed from 10 years of satellite data (2002 − 2011). Since 2011, there have been 3 years with severe blooms (2013, 2014, and 2015) and 1 year with a small bloom (2012), providing important new data. In addition, Obenour et al. (2014) concluded that the blooms may have become more sensitive to phosphorus loads than earlier in this century. Also, the work of Baker et al. (2014a, 2014b) indicated the potential importance of differing forms of bioavailable phosphorus. The combination of these factors led to the realization that the relationships between HAB intensity, and the driving factors of phosphorus loading and river discharge should be reexamined in order to reevaluate the original loading models (Stumpf et al., 2012). This paper examines the models for estimating bloom severity using data from 2002 to 2015 along with measures of bioavailable phosphorus in order to identify improvements in forecasting bloom severity and evaluating the impact of phosphorus loads for management strategies.

Methods

Biomass estimation

Bloom biomass was determined using data from the Medium Resolution Imaging Spectrometer (MERIS) for 2002–2011. After MERIS's satellite failed in April 2012, the Moderate Resolution Imaging Spectroradiometer (MODIS) was employed for 2012–2015. Both

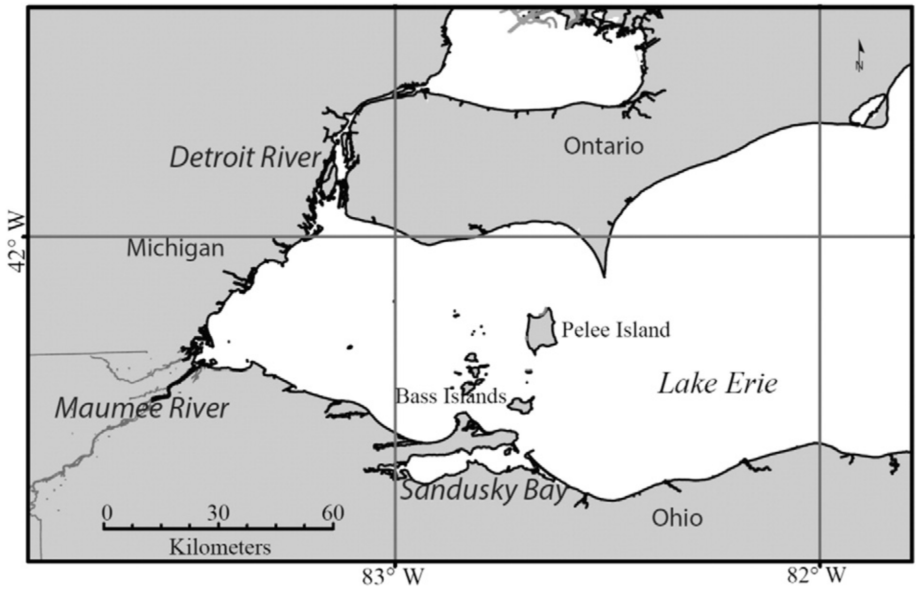

Fig. 1. Western Lake Erie location.

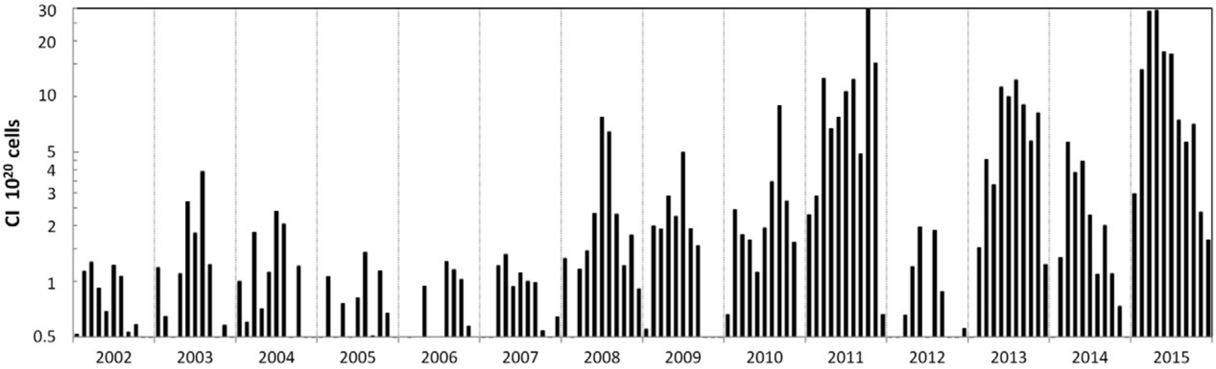

Fig. 2. Time series of the total biomass measured as CI based on the 10-day composites. Eleven periods cover each year, starting July 11 and ending October 31. Threshold at CI = 0.5 for readability (note the log scale).

satellite data sets were processed using a spectral curvature method to obtain the cyanobacterial chlorophyll-related index (CI) as described by Wynne et al. (2013b), who also showed that a simple multiplier to the MODIS curvature allows the MODIS and MERIS data to be directly matched. The CI calculations used radiance-based reflectance, which formally has units of sr^{-1}. Several MODIS bands tend to saturate over “scum” areas (areas with dense accumulations on the water's surface), requiring a switch to an infrared algorithm that is tuned to match the CI in the overlap in blooms in non-saturated areas (Wynne and Stumpf (2015). Both MODIS and reduced resolution MERIS data have a nadir pixel view of about 1 km and were mapped to a common Albers equal area projection with nearest neighbor interpolation. The CI corresponds to *Microcystis* biomass, with CI of 0.001 sr^{-1} corresponding to 10^5 cells mL^{-1} (Wynne et al., 2010; Lunetta et al., 2015). If the surface concentration is assumed to be one meter deep (the maximum depth of detection), then an accumulated CI of 1.0 units corresponds to 10^{20} cells (Stumpf et al., 2012).

Composite images of the maximum CI value at each map pixel were obtained from the individual scenes within sequential (non-overlapping) 10-day periods (Wynne and Stumpf, 2015). The maximum was used for these 10-day composites for two purposes. First, the integration removes most clouds over the period. Second, the satellite observes only the surface concentration, nominally within a meter of the surface, as noted above. As *Microcystis* blooms tend to float to the surface during calm weather, accumulating the biomass at the surface, choosing the maximum CI gives the best estimate of the areal biomass during the 10-day period. Ten days are a reasonable compromise between frequency of recovery and temporal resolution (Stumpf et al., 2012). All the pixels for the western basin were then summed to obtain the total biomass in CI units for each 10-day period (Fig. 2; values given in Electronic Supplementary Material (ESM) Table S1).

Stumpf et al. (2012) used the average of three highest consecutive 10-day periods to define the annual bloom magnitude (that will be called CI-avg). This average gave an estimate of severity over the worst “month.” However, if any of the three 10-day periods suffered from a lack of usable days due to cloud cover, that 10-day composite may underestimate the areal biomass, particularly if only one usable day occurred and it was concurrent with strong winds. This could produce a low bias (underestimate) of the average areal biomass occurring over the 30 days. An alternative approach is to use the 10-day period with the maximum biomass to capture the best estimate of the amount of actual cyanobacterial biomass for comparison with the seasonal phosphorus load. The peak in biomass also typically occurs in August or September, after the seasonal load (Stumpf et al., 2012). Accordingly, to address the total biomass, this study uses the maximum single 10-day period (CI-max) (Figs. 2 and 3). Yet it is important to note that the CI-avg. and CI-max are closely matched, with a linear regression r^2 of 0.92 and a mean absolute percentage difference (MAPE) of 15% and CI-max = 1.68 × CI-avg.

The accumulated CI has some uncertainty, especially in how pixels next to the shore are evaluated (either excluded or included), as these pixels can have either dense blooms or erroneously high values. As a

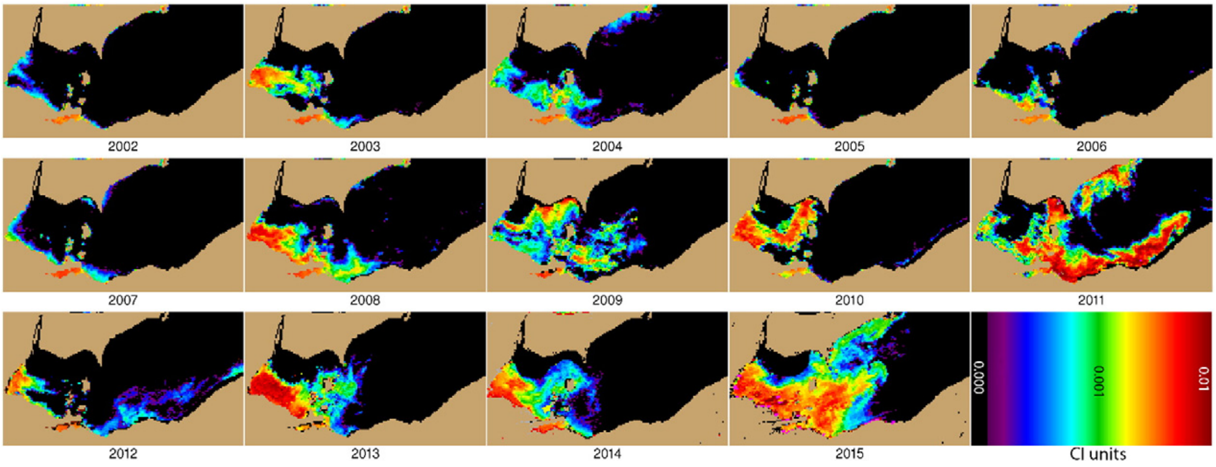

Fig. 3. Bloom pattern at peak biomass for each year. Green (in center of scale bar corresponds to threshold of hazardous bloom (CI = 0.001, Stumpf et al., 2012).

result, the minimum uncertainty is about 0.5 CI units (i.e., negligible separation between 2005 and 2007), with an additional uncertainty of 10% of the total CI for MERIS and about 25% for MODIS. MODIS is a noisier sensor and requires more processing and adjustment to correct for saturation and faulty nearshore values.

Nutrient loads and discharge

Stumpf et al. (2012) found that bloom severity could be explained by models using monthly discharge and phosphorus loads (total phosphorus and dissolved reactive phosphorus) for the Maumee River (Stumpf et al., 2012; Kane et al., 2014). The Maumee River is the largest tributary in the Great Lakes basin. While the Maumee has 1/35th the flow of the Detroit River, which carries water from Lake Huron and the upper Great Lakes (Wynne and Stumpf, 2015), the Maumee's large concentration of phosphorus means that the two rivers supply an equal amount of the phosphorus load into Lake Erie (Dolan and Chapra, 2012; Scavia et al., 2014). The other tributaries into the western basin are negligible, with <1/10th the loads of the Maumee.

Phosphorus loads were obtained using data from the Heidelberg Tributary Loading Program (HTLP) operated by the Heidelberg University's National Center for Water Quality Research (NCWQR) (Richards et al., 2009). Water samples were collected for suspended sediment and nutrient analysis at the USGS gaging station (04193500) on the Maumee River at Waterville, OH, 42 km upstream from the lake. Three samples per day were collected using a refrigerated ISCO autosampler. During periods of high flow or high turbidity, all samples were analyzed; at other times only one sample per day is analyzed. Typically, this program provides 450 to 500 analyzed samples per year (Heidelberg, 2015). Discharge was determined from the USGS data. Monthly loads were calculated as the sum of daily loads (Richards et al., 2009). Any days with missing flow weighted mean concentrations (<5% of the time) were interpolated from previous days.

Bioavailable phosphorus was determined from TP, DRP, and the coefficients of Baker et al. (2014a). Baker et al. (2014a) found that the unreactive phosphorus is a negligible component of the dissolved phosphorus. Therefore, total particulate phosphorus (TPP) was determined as the difference between TP and DRP (TP − DRP) following Baker et al. (2014a). Total bioavailable particulate phosphorus (TBPP) was then calculated from the Waterville TPP as

$$\mathrm{TBPP} = \beta \times \mathrm{TPP} \quad (1)$$

where β is the proportion of the TPP that is bioavailable (0.26), with the value for β obtained from Baker et al. (2014a). As particulate phosphorus is lost by settling between Waterville and Maumee Bay, the residual ($\mathrm{TBPP_{resid}}$) that reaches the lake was determined by

$$\mathrm{TBPP_{resid}} = (1\text{–}S) \times \mathrm{TBPP} \quad (2)$$

where S is the settling term, or the proportion of TPP that settled out of the water. Baker et al. (2014b) showed that approximately 70% of the TPP settled out following a storm event in late August 2007. The total bioavailable phosphorus entering Lake Erie from the Maumee River is then the sum of the DRP and $\mathrm{TBPP_{resid}}$:

$$\mathrm{TBP} = \mathrm{DRP} + \mathrm{TBPP_{resid}} \quad (3)$$

To better understand the influence of the bioavailable term (β) and the settling term (S), the sensitivity of the TBP was examined. In these sensitivity tests, β covered the range from 0. 2 to 0.3 (Baker et al., 2014a) and S covering the range from no settling (S = 0) to complete settling (S = 1.0). Loads and CI values are found in Tables S1 and S2.

Water temperature

Water temperature was determined using MODIS thermal data from 2002 to 2014. Monthly averages were obtained from the Giovanni web site (NASA, 2015) for the southern section of the western basin west of 82.741 W (Marblehead) and south of 41.914 N (latitude of north end of Pelee Island). The satellite collects data about 2:00 am and 2:00 pm local time. The night and day data sets were obtained separately and compared. While they capture variations caused by diurnal heating, the two sets differed <1°C across the entire time period, no larger than the uncertainties in the measurement.

Analysis methods

Following Stumpf et al. (2012), we examined the non-linear relationships of CI-avg. and CI-max with accumulated monthly spring discharge (Q) as well as TP, DRP, and TBP loads. All of these relationships between the loads or discharge and the bloom magnitude are approximately exponential; thus, log transforms were applied to the biomass data (i.e., $\log_{10}(\mathrm{CI})$ against TBP) to allow for parameterization using standard least squares linear regression. The resulting models have the following form:

$$\mathrm{CI} = \mathrm{B} \times 10^{(aX)} \quad (4)$$

where X is the input variable (discharge, TP, DRP, or TBP), and a and B are parameters obtained from linear regression. For consistency in comparing the plots, 70% variation in the slope is plotted, as this value captured the inter-quartile range of misfit of observed to regression values in the best models. Mean absolute deviation (MAD) and standard deviation (SD) were determined between the modeled and observed CI in order to assess error and robustness of the models. These excluded the two extreme load years: the lowest (2012) and the highest (2015), both of which were anomalous in several ways, as discussed in the Results and Discussion sections. The MAD provides a better metric for non-normal distributions, e.g., ones with some large misfits (Gorard, 2005; Willmott and Matsuura, 2005), while the SD is a familiar metric. Spearman rank correlation (rho) was applied to the bloom years (2003, 2004, 2008–2011, 2013–2015) to evaluate the effectiveness of the models in determining the relative size of the blooms. The sensitivity of TBP to variations in the values of bioavailable (B) and settling (S) was also considered.

Results

Stumpf et al. (2012) determined that total discharge from March through June provided the best metric for estimating bloom magnitude for 2002–2011. Likewise, the TP and DRP loads for March–June had the best relationships with the CI (TBP was not examined in that paper nor in Obenour et al., 2014). The CI-max showed weaker relationships for March through June discharges and phosphorus loads when 2012 to 2015 data were included (Table 1, Fig. 4) because the 2012 and 2013 blooms were larger than expected compared to the other years. The 2014 bloom falls within the 2002–2011 data.

Because western Lake Erie blooms establish in July (Bridgeman et al., 2013) and peak in late August or early September (Wynne and Stumpf, 2015), we examined the relationships between CI-max and nutrient loads from March through July to assess the influence of July in explaining the recent blooms. July had relatively large TBP (and discharge) in 2003, 2008, 2013, and 2015 (Fig. 5). By including the July loads, the 2013 bloom was slightly better modeled (Fig. 4B); however, the 2003 bloom was not, and 2003 had a bloom much smaller than expected from either discharge or any phosphorus load (Fig. 4B). The Discussion section will further consider variations in 2015. The model error increases for all loads (Table 1). The 2008 bloom shows a slight difference when including July loads.

Table 1
Mean absolute deviation (MAD) in CI units and Spearman's rho for the several models for each of the variables, load of Q (10^6 m^3), TP, DRP, or TBP (metric tons).

	MAD				Spearman rho			
	Mar–Jun	Mar–Jul	Mar–Jul warm	Mar–Jul wgt	Mar–Jun	Mar–Jul	Mar–Jul warm	Mar–Jul wgt
Q	1.8	2.4	2.3	2.0	0.75	0.62	0.87	0.93
TP	2.2	2.8	2.7	2.8	0.48	0.55	0.55	0.73
DRP	2.6	3.6	2.4	2.3	0.70	0.58	0.68	0.87
TBP	2.2	3.3	2.0	1.9	0.70	0.63	0.72	0.87

As temperature is important for cyanobacterial growth, the western basin water temperatures were examined to better understand why the 2003 bloom was small for the March to July TBP (Fig. 4B). In 2003 and 2008, June was much colder (17.7 °C in 2003; 16.7 °C in 2008) than in the other years (all above 20 °C; Fig. 6). By contrast, 2013, which had similar loads prior to July, had a mean temperature of 21.3 °C. Cyanobacteria favor temperatures above 20 °C (Imai et al., 2009; Paerl and Huisman, 2009), indicating growth would have been depressed by cold temperatures in early summer during 2003 and 2008. Cold temperatures may also represent a surrogate for a combination of factors, like strong winds and cloudy weather that can also reduce cyanobacterial growth. Under conditions associated with June temperatures <20 °C, the growth of *Microcystis* may be delayed and cells are not present to use the July loads. The relationship between CI-max (bloom biomass) and TBP improved when including July only during warm (June) summers (Fig. 4C, Table 1). The 2013 bloom was still smaller than modeled, as was 2012, which had no significant load in July. Including August discharge or loads (not shown) did not improve the models, possibly because of nutrient limitation (Chaffin et al., 2014). More likely, August was not important because August loads were negligible in all years—except 2007 (Baker et al., 2014b) when the spring loads and bloom were also minimal—also suggesting that the lack of early season growth limits the use of the late season nutrients.

Because the bloom develops rapidly during July and August (Bridgeman et al., 2013), the July phosphorus loads during normal warm temperatures may have a larger influence on the bloom biomass than the previous months (March through June) (Chaffin et al., 2011). Namely, some of the phosphorus provided to the lake from March to June may be lost to the eukaryotic phytoplankton before the cyanobacterial bloom starts. Indeed, by reducing the influence of March through June loads by half and using the entire July load at normal temperature (Fig. 4D, Table 1), the model has the best fit with all years, except for 2012 (and 2015, addressed in Discussion). This result raises a question about the timing of bloom initiation. If July loads are a factor, then the possibility exists that the loads only during June and July would drive the blooms. Stumpf et al. (2012) observed that June loads alone might explain most years except 2004 and 2011. The combined load from June and July, however, does not provide a meaningful pattern compared to the bloom biomass (Fig. 7), with similar results for the other loads. Extremely low TBP loads for June and July (<20 metric tons; hereafter m. tons) corresponded to smaller blooms, with no pattern for the larger blooms. In fact, 2011, one of the two biggest blooms, had one of the smaller loads in June and July.

The models applying the March through July loads, with the exclusion of July in cold Junes, best described the observed biomass (Fig. 4C, D). Table 2 gives the parameters (B and a) for Eq. (4) for the equally weighted March to July and the March to July with reduced weight for March to June.

Sensitivity

The results shown here were mostly insensitive to variations in the bioavailable fraction (β) of phosphorus (Eq. (1); ESM Fig. S1) or in the settling rate (Eq. (2); ESM Fig. S2). The range of the bioavailable fraction

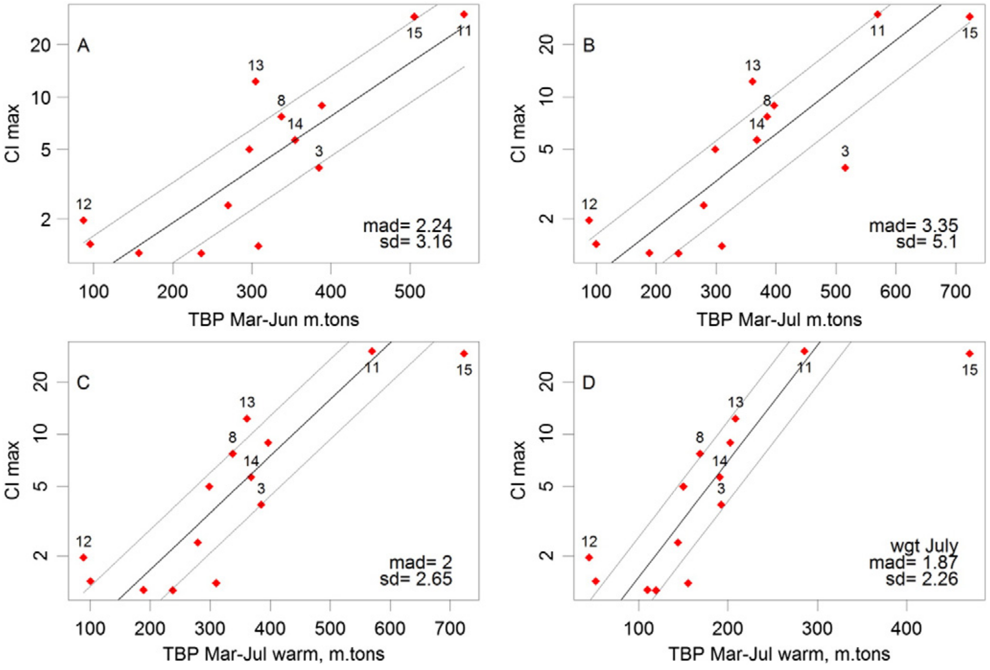

Fig. 4. Relationships between total bioavailable phosphorus (TBP, which includes settling correction of Eqs. (2)–(3)) and biomass (CI units where CI-max = 10^{20} cells) for March to June (A), March to July (B), and March to July, with July included only for warm Junes (C), and with the same parameters as (C) but with March to June loads weighted at ½ of July (D). Dark line is relationship with values shown in Table 2. Thin lines show ±70% of slope. The MAD and the SD are the mean absolute deviation and standard deviation of observed against the regression line, excluding 2012 and 2015. Loads are given in metric tons.

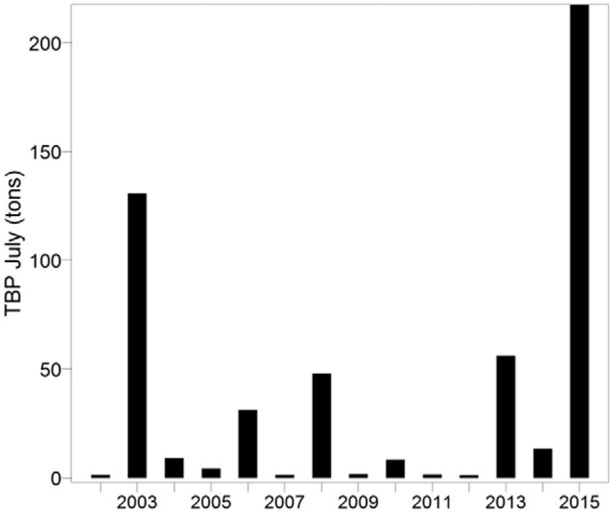

Fig. 5. July load (metric tons) of total bioavailable phosphorus.

(β) of TBPP of 0.2 to 0.3 reported in Baker et al. (2014a) results in a variation of 5% in TBP, which is negligible in the model (ESM Fig. S1). Larger variations in β are not warranted (Baker et al., 2014a). The settling rate of suspended sediment and associated particulate phosphorus (between the sampling station at Waterville, OH and Lake Erie proper) had only a slight impact on the error terms with the mean absolute difference (MAD) of 1.87 for $S = 0.3$, and a MAD of 1.67 for $S = 0.5$ and $S = 1.0$. The largest differences in the models occurs with total settling (MAD = 2.3). Complete settling or no settling are unrealistic and have not been observed in this system (Baker et al., 2014b) The likely settling residual is more realistically between 0.3 and 0.5, which contributes at most a 10% change in TBP, which would lead to low uncertainty in the models.

Discussion

The bloom size was best modeled using discharge and TBP loading from March through July, with July excluded only when June water temperatures were below the optimal temperature (20 °C) for *Microcystis* growth (Imai et al., 2009; Paerl and Huisman, 2009). Discharge, *Q*, continued to provide the best predictor of the annual bloom biomass. While the uncertainty (MAD) with *Q* is slightly higher than for TBP, *Q* is superior at determining the relative size of the blooms (Spearman rho in Table 2). Discharge, of course, is not, by itself, useful for a management strategy. Of the phosphorus metrics (Table 2), TBP explained the bloom biomass well and better than a TP model, both as estimated and for relative size (Table 2). This result was expected; the bioavailable phosphorus that reaches the lake is the ecologically relevant load, and so provides the information critical for nutrient management strategies.

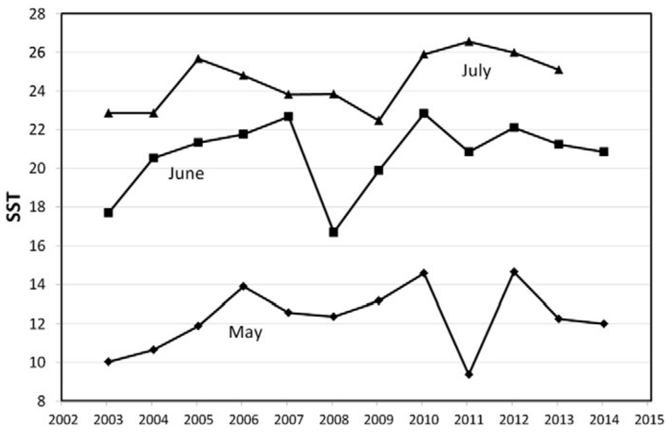

Fig. 6. Western basin average monthly water temperature for May, June, and July from 2002 to 2014.

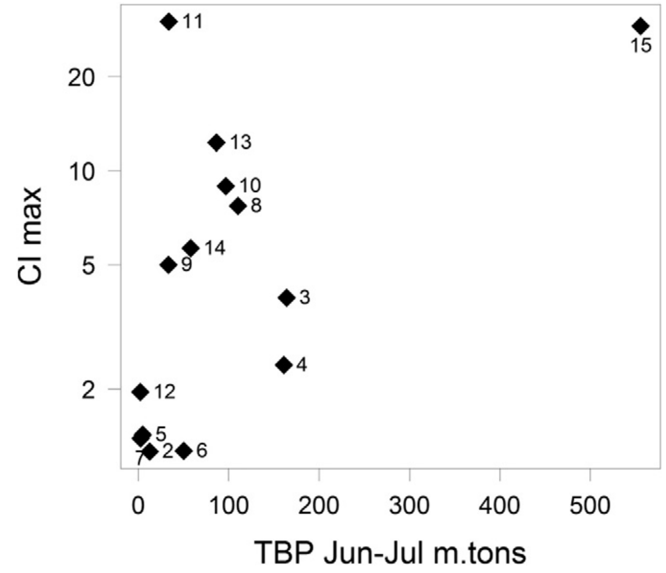

Fig. 7. The lack of a relationship between the bloom severity (CI-max) and the combined June and July TBP loads only in metric tons (without March to May loads).

Several significant questions arise from these results: (1) What is the appropriate model for predicting annual bloom severity, and should the original March to June model used by Stumpf et al. (2012) and Obenour et al. (2014) be replaced? (2) What is the appropriate choice of phosphorus loading for target scenarios? (3) Do the results support a trend over time that yields larger blooms relative to phosphorus load as proposed by Obenour et al. (2014)? (4) Are there details we still do not understand after the inclusion of 2012–2015 data? Our answers to these questions follow below in numerical order.

Annual bloom severity

For assessing annual severity, the results indicate that a model based on TBP for March to June, which was the recommended model of Stumpf et al. (2012), was insufficient with the additional data, because it under predicts the blooms of 2012, 2013, and 2015 by not including July loads. When including July, models using TBP loads best approximate the interannual variability in the bloom biomass, compared to TP or DRP loads (Tables 1 and 2, and Fig. 8). Of particular note, TP loads provided poorer discrimination between all of the blooms (CI >2) compared to TBP (or DRP) loads, with consistently lower Spearman's rho (e.g., 0.73 vs 0.87 for TBP for weighted March to July). Also, parameterization with least squares regression led to fits that were strongly leveraged by 2005 (the smallest load used in the regression) and 2011 (the largest load used). Using models constructed with those 2 years excluded, the TP model changed drastically and completely over-

Table 2
Coefficients for the March to July unweighted and weighted models with CI-max (Figs. 4 and 8). "Unweighted" and "weighted" are March to July models with warm June. March to June (for reference against Stumpf et al., 2012) and March to July without temperature change are shown for completeness. Coefficients *B* and *a* are from Eq. (4): CI biomass = $B \times 10^{(a\ X)}$, where *X* is the total load of *Q* (10^6 m^3), TP, DRP, or TBP (metric tons).

	Unweighted		Weighted		Mar–Jun		Mar–Jul	
	B	$a \times 10^{-3}$	*B*	$a \times 10^{-3}$	*B*	$a \times 10^{-3}$	*B*	$a \times 10^{-3}$
Q	0.11	0.503	0.081	1.05	0.27	0.401	0.23	0.392
TP	0.40	0.864	0.31	1.85	0.57	0.748	0.55	0.713
DRP	0.38	4.12	0.34	8.30	0.48	3.87	0.55	3.30
TBP	0.37	3.26	0.32	6.67	0.47	3.06	0.51	2.70

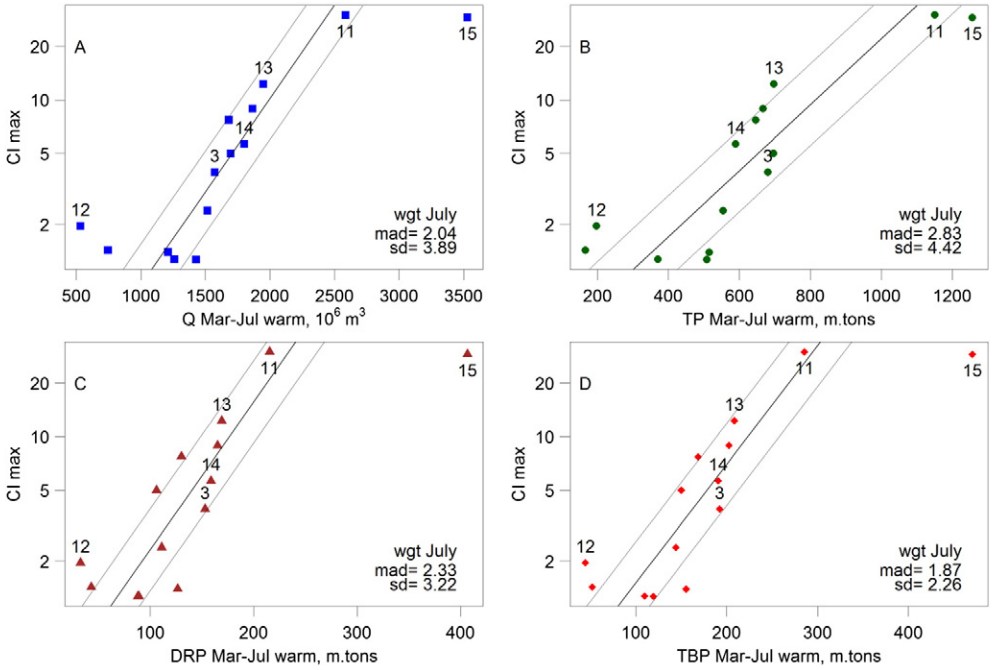

Fig. 8. Relationships between CI-max and March to July, with July included only for warm Junes and March to June loads (in metric tons) weighted at ½ of July for (A) discharge (Q), (B) TP loads, (C) DRP loads, and (D) TBP loads.

predicted 2011, whereas DRP and TBP models still closely predicted 2011 (Table 3).

The nutrient load through July should be considered because cyanobacterial growth typically starts in Lake Erie by the beginning of July (Bridgeman et al., 2013), although it intensifies in August in most years (Wynne and Stumpf, 2015). Cyanobacteria are available to take advantage of the fresh supply of TBP. If cyanobacterial growth starts later because of a cold early summer (e.g., in 2003), excluding the loads for July may be an appropriate model component. This hypothesis can be examined more specifically with deterministic models, such as that of Verhamme et al. (2016-in this issue). The temperature exclusion may become irrelevant in the future if climate change leads to consistently warm Junes. In the new analysis, loads from March through July had the best relationship with the total biomass, although 2015 would be overestimated. Because these months cover an ecologically appropriate time period, subsequent forecast models should use March through July for predicting the seasonal cyanobacterial bloom. Only 1 year, 2007, had a large nutrient load in August and that year had one of the smallest blooms, even in September (Figs. 2 and 3).

Most appropriate P fraction

Historically, the evaluation of phosphorus load impacts in aquatic systems has focused on TP rather than on the bioavailable forms of phosphorus because virtually all TP from point sources was bioavailable (Baker et al., 2014a). By contrast, phosphorus draining nonpoint sources tends to consist primarily of sediment-bound TPP, which is much less bioavailable (Baker et al., 2014a). True bioavailability should include only that phosphorus that is both chemically and spatially bioavailable. Settling determines spatial bioavailability; most phosphorus bound to suspended sediments does not reach the lake and is not available for bloom development under any conditions. Because the mean spring DRP load is 27% (range 15–38%) of the TP load at Waterville, the Maumee River delivers nearly equal amounts of DRP and TPP to Lake Erie; as a result, the TBPP load is less than the DRP load. Varying the proportion of TPP that settled during delivery (S) should produce only slight variations in the amount of TBP (ESM Fig. S2), as DRP load component of TBP is greater than the TBPP component.

Table 3
CI prediction of 2011, and percentage of predicted to observed 2011, for regression parameterization excluding 2005 and 2011. Observed CI-max for 2011 was 29.1.

Model	Mar–July unweighted (%)	March–July weighted (%)
TP	105 (360%)	160 (550%)
DRP	23 (79%)	21 (72%)
TBP	27 (93%)	26 (91%)

Increasing sensitivity to P loads?

Obenour et al. (2014) concluded that the HABs appear to be more sensitive to recent loads compared to the past decade; the results here do not support this conclusion. Even though the models would underestimate the 2012 bloom, and the 2013 bloom would be underestimated in some models, the 2014 bloom was indistinguishable from the other past blooms, and 2015 bloom would be overestimated by most models. At this time, evidence does not support the hypothesis of increasing sensitivity over time of the bloom growth to phosphorus loads.

An additional consideration on trends is the temporal pattern in discharge over the 13 years studied here. The first 6 years (2002–2007) had five of both the smallest discharges (and P loads) and the smallest blooms. The last 8 years (2008–2015) had all but one of the seven largest loads and seven largest blooms. This disparity can lead to a conclusion that there is a trend toward increasing bloom intensity. While a trend is possible, this pattern may also be a result of cyclicity in precipitation. Nevertheless, higher discharges and phosphorus loads of recent years also approximate conditions that are predicted to be more common with climate change (Hayhoe et al., 2010; Stow, 2015). In fact, precipitation and discharge have increased in the Maumee River basin over the last several decades (Stow, 2015), and climate change models forecast more frequent intense rainfalls in the region (Michalak et al., 2013). These climatic factors do not mean that a given phosphorus load will produce larger blooms in the future, but they do suggest that larger loads may become more common, increasing the risk of larger blooms.

Need for increased understanding

What other factors are still not understood? Each of the outlier years may provide information that lead to hypotheses that can be tested in the future with more data, or with other types of models. The most striking outliers are 2003, 2012, 2013, and 2015. In 2012, the bloom was larger than expected given the extremely small loads (lowest of all 13 years), but 2012 was also the only year that a small load followed a year with a massive bloom. The 2011 bloom may have had a residual impact on 2012, either in residual cyanobacterial cells or in excess phosphorus available for internal loading. In 2012, the central basin also had the largest measured hypoxia zone (Zhou et al., 2015), indicating unusual conditions that year. At this point, testing a residual impact requires the occurrence of another drought year following a severe bloom. To further complicate 2012, Lake Erie was ice-free in the preceding winter (2011 − 2012), an uncommon event that occurred in one other year (2006) in this time series (Bai et al., 2015).

The other outlier years have commonality in July loads. Of these, 2013 has no obviously unusual characteristics, except for the large July load. In 2003, the bloom tended to be smaller than expected when compared to the equivalent large bloom years and to the model relationships. Though the *Microcystis* biomass measured by Bridgeman et al. (2013) indicates a locally strong and persistent bloom in 2003, the measurements from the satellite do not appear to be an underestimate as the bloom was localized primarily in and around Maumee Bay (Stumpf et al., 2012). A chlorophyte bloom was still present in the first week of August (Fahnenstiel, personal communication), and 2003 was cold in May as well as June (Fig. 6). Furthermore, 2003 was the first time in several years that a severe *Microcystis* bloom occurred in western Lake Erie. The combination of these factors suggests that 2003 was anomalous in several ways, possibly contributing to the proportionately mild bloom. The other year with a cold June 2008, shows a smaller anomaly, but this is consistent with the smaller July load in 2008.

The 2015 bloom

The 2015 event pushed the limits of the system and models. The monthly discharge was a record for June and the third greatest monthly discharge since the USGS began collecting data in 1939. Even the July load (Fig. 5, ESM Table S2) was larger than the entire March–July load for three of the years (Fig. 4B). Unlike all other bloom years (Wynne and Stumpf, 2015), the 2015 bloom started near the islands rather than near the Maumee River mouth and did not appear in the far western lake until weeks later. This was likely due to light limitation from high turbidity associated with the storm event runoff and possibly the change in timing and spatial distribution of the phosphorus loads. The maximum bloom occurred in August, whereas other major bloom years had a maximum bloom in September (Fig. 2). The dense scum that formed over a large part of the western basin (NOAA, 2015) may have led to an underestimate of the total biomass because the satellite data cannot capture more information once scum completely covers the entire area of water observed in each pixel. While 2015 fits a March to June model (Fig. 4A), these many anomalous aspects of the 2015 bloom raise doubts about recommending a model based on the fit of 2015.

The 2015 observations also suggest a limit to the non-linear relationship between phosphorus load and biomass. An ecological reason for the observed non-linearity is suggested by the strength of discharge alone as a biomass predictor. If the Maumee phosphorus is dispersed over a large area as a result of large discharge, then the bloom can also develop over a larger area. As a result, the cells will have access to more ambient phosphorus that did not discharge from the Maumee River, leading to a non-linear relationship with Maumee phosphorus loads. Eventually, growth must slow due to limitation of available phosphorus or other factors like light, nitrogen, or micronutrients. The resultant curve would resemble a familiar logistic growth model, with 2015 falling within the reduced growth phase. (As the 2011 bloom peaked in the central basin, the bloom that year may have accessed more central basin “non-Maumee” phosphorus than in other years, leading to more biomass than might otherwise have occurred as suggested by Obenour et al., 2014.) While a logistic function could be fit through the data, there are too few data points to achieve a robust relationship for such a model. A logistic function may improve prediction of the extreme blooms like 2015, but it would not improve the understanding or prediction of the load response for the moderate blooms until we have more years of data.

Flow weighted mean concentration

The spring (March to July) flow weighted mean concentration (FWMC) of TBP from the Maumee River is near 0.10 mg L^{-1} (Fig. 9), which is the TP concentration that Downing et al. (2001) found was present when cyanobacterial dominance was most likely. This concentration is much higher than what was observed in the 1990s because the FWMC for DRP approximately doubled from then into the present century (Baker et al., 2014a). Our models are not currently based on FWMC, in part because FWMC has not changed drastically in the period of time with concurrent satellite bloom estimates. Therefore, discharge and phosphorus loads are all correlated. While discharge provides the best model of the bloom intensity for an annual forecast, it is not the most useful for setting nutrient reduction targets. The effectiveness of discharge for predicting the annual biomass suggests that discharge implicitly describes dispersion of phosphorus across the lake with that dispersion potentially more important than the small interannual variations in FWMC. One hypothesis for future scenario modeling for phosphorus is to simply apply the (updated) average FWMC to the discharge as a predictor. We anticipate that large changes in FWMC would cause shifts in the modeled blooms compared to the current time period, and FWMC can be influenced by management strategies, unlike rainfall or discharge. Scenario forecasting efforts should use TBP models to estimate bloom biomass, although seasonal predictions can be made with discharge (Figs. 4C, D and 8A, Table 2). Further investigation of weighting factors for March to June will require other types of

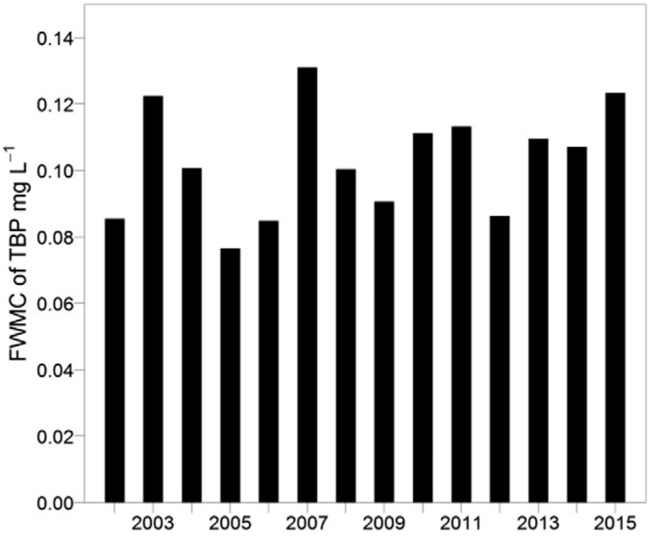

Fig. 9. Flow weighted mean concentration (FWMC) of the total bioavailable phosphorus for March to July.

models as there are insufficient observations to parse annual patterns with statistical climatological models. Evaluation with other models may become important if future years have large loads in July. Future efforts should closely monitor the FWMC for bioavailable phosphorus for changes from the past 15 years.

Conclusions

The models developed here for western Lake Erie HABs can be used for two core purposes: forecasting the severity of the seasonal bloom and evaluating scenarios that would reduce the severity of HABs. While both discharge and TBP loads from March through July were good predictors of the biomass, they serve different purposes. Whereas discharge continues to produce the least uncertainty in estimating the relative annual bloom biomass, TBP provides the best information on phosphorus loads suitable for bloom reduction strategies. Hence, strategies for reducing the flow weighted mean concentration of TBP will have the largest influence on reducing the severity of HABs. As the typical DRP concentration in the lake is below 0.02 mg L^{-1}, a reduction in the phosphorus concentration entering the lake will likely reduce the area of the lake with concentrations that favor cyanobacterial blooms (Downing et al., 2001), regardless of the river discharge. Because DRP comprises most of the bioavailable phosphorus entering the lake, reducing the FWMC of DRP should be a critical component of the phosphorus management plans, such as the Great Lakes Water Quality Agreement (GLWQA, 2012). Future research should continue to examine the composition of TP as well as the bioavailability of particulate phosphorus. FWMC should continue to be examined in detail, as it provides an indicator that can be influenced by management strategies.

For understanding drivers of aquatic health, empirical models have a particular value in defining the actual conditions and providing a contrasting reference to deterministic simulation models such as the WLEEM and ELCOM-CAEDYM used in Lake Erie (Scavia et al., 2016-in this issue; Verhamme et al., 2016-in this issue). Nevertheless, outliers may exist for a variety of different ecological factors and care must be used to avoid over-fitting or over-interpretation of the data. Continued monitoring of both tributary loads as well as the size of the bloom using satellite imagery should help us observe unique patterns that point to causes of these outliers. Each subsequent year of data will lead to understanding of the impacts of new nutrient management strategies on the timing of loading and bloom development. These models point to the essential role that monitoring the health of our aquatic ecosystems can play on ecological, economic, and social systems.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jglr.2016.08.006.

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